A Structural Analysis of the Default Swap Market – Part 2 (Relative Value)*

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Abstract

We evaluate several long/short strategies for managing a portfolio of default swaps. The strategies are based on a ranking of credits by residuals, which are the differences between market spreads and spreads generated by the iSpread structural model. Investment grade portfolios for the U.S. and Europe earned an average of 70 basis points for each long dollar notional between January 2004 and December 2006. Non-investment grade portfolios earned 321 basis points averaged over the same regions and time period. Transaction cost estimates based on scenario analysis ranged from 19 to 27 basis points for investment grade and 26 to 54 basis points for non-investment grade portfolios. Strategies that aim to mitigate transaction cost by holding trades with little profit showed mixed results.

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1 Introduction

The default swap market provides investors with a means to take positions on credit risk and to hedge it. The size and breadth of the market together with the liquidity and standardization imparted by the CDX and ITraxx indices make credit attractive to a broad spectrum of investors, ranging from pension fund managers to derivatives traders.

In this article, we evaluate the information content of the iSpread model developed in Goldberg et al. (2007) through the lens of several default swap trading strategies. iSpread is a two-factor structural model of the default swap spread market that provides estimates of credit spreads for approximately 6500 names in the U.S. and Europe on a daily basis.

The strategies we consider are based on the information contained in residuals, which are the differences between market and model spreads. Using techniques from active portfolio management, we analyze the strength of the residuals as trading signals by comparing them to the residual return of individual credits with respect to indices based on region, sector, and coarse quality. We calculate ex-post information ratios for four portfolios based on region and quality (US Investment Grade, US High Yield, Europe Investment Grade, and Europe Unrated) and aggregate them on an annual basis. Information ratios were positive for all four portfolios in 2005 and all but Europe Unrated in 2006. The highest information ratio of 4.4 was obtained for the EU Investment Grade portfolio in 2006. Details of the calculation and a more complete review of the results are in Section 3 and Figures 2–4.

In Section 4, we describe portfolio construction methods compatible with the information contained in the residuals. The basis of all the strategies we consider is described in Section 4.1. Credits are ranked by residual. The *cheap* credits have the largest residuals: the difference between the market and model spreads is greatest. The *rich* credits have the smallest residuals. We construct rich/cheap portfolios determined by region, coarse quality, and sector, and we rebalance every month by selling protection on credits in the cheapest quartile and buying protection on credits in the richest quartile. Importantly, estimates of the model that guide each portfolio rebalancing are based completely on prior information. Hence, the strategy results are out of sample in the strictest sense.

We implement several instances of the base strategy, varying the portfolio rebalancing rules and transaction cost scenarios. Strategy results are presented for the period January 2004 to December 2006 whenever possible and January 2005 to December 2006 when data are constrained. Earnings are expressed in basis points per long (or cheap) dollar notional.

In Section 4.2.1 and Figures 5–9, we describe a carry-neutral strategy without transaction costs. The strategy generated significant return for most portfolios, with the greatest gains in excess of 500 basis points per long dollar invested achieved by the US High Yield portfolio in 2004, corresponding to an information ratio of 1.7. A severe loss of 275 points per long dollar invested was realized in the US Investment Grade Consumer Discretionary sub-portfolio in 2005. A large portion of the loss was accrued during spring 2005 in connection with downgrades to General Motors and Ford. In spite of this loss, the overall information ratio for the US Investment Grade portfolio in 2005 was 0.6. An analogous strategy based on beta-neutrality showed very similar results, which are reported in Section 4.2.2 and Figures 13 and 14.

During the study periods, the carry-neutral strategy generated turnover at approxi-

mately 30% per month. Data constraints prevent us from adjusting the results to reflect trading costs in a precise way. Therefore, to analyze the impact of transaction cost, we provide several scenarios based on market bid/offer spreads. These are described in Section 4.3 and Figures 15–19, and their effect on the carry-neutral strategy is reported in Section 4.4.1 and Figures 20–27. The transaction costs eroded relatively little of the profit for the high yield portfolios. The carry-neutral US High Yield strategy obtained ex-post information ratios ranging from 0.6 to 0.7 in 2005 and 0.85 to 1.0 in 2006. However, transaction costs presented a more serious consideration for investment grade portfolios. Nevertheless, the carry-neutral US Investment Grade strategy adjusted for transaction costs obtained ex-post information ratios ranging from 0.2 to 0.3 in 2005 and 0.6 to 0.7 in 2006.

In Section 4.4.2, we explore a modification of the transaction cost adjusted carry-neutral strategy intended to mitigate the impact of trading on profits. The rebalancing rules are modified so that a trade is executed only if the profits or losses exceed a fixed multiple of transaction costs. The results of this modification, shown in Figures 28 and 29, are mixed.

Overall, the rich/cheap strategies based on the iSpread residuals generated significant profits and high information ratios during the study period.

1.1 Related Literature

In this section we provide a brief review of related literature.[1] Tindlund (2006) tests the performance of default swap portfolios constructed using model spreads derived from default probabilities sourced from Moody's KMV. The model spreads are estimated using a linear regression between market spreads and spreads derived directly from the default probabilities. Residuals are ranked and the performance of the top and bottom quintiles is tracked over the period 2001–2005. Similar to our findings, the author reports that overpriced (cheap) spreads tighten to an extent that would result in a decrease in the carry of 2.9% monthly compared to changes in carry of an index portfolio, while underpriced (rich) spreads widen so that carry is increased 2.2% monthly net of index changes. Portfolio notionals are standardized so that all portfolios have equal carry at the beginning of each period. While this performance is stronger than what we find for some of our region-quality groups, the author notes that performance during the second half of the study period (mid-2003–2005), which overlaps with part of our study period, was weaker than in the first half. Agrawal et al. (2006) also use Moody's KMV default probabilities to construct a model of corporate bond spreads and test model performance of quartile strategies over the period 1999–2003. They report an annual return of 6% (600 basis points) over their study period. Zhu (2006) extends this analysis to other trading strategies. These results point to the fact that returns from such strategies are likely to be higher during periods where default swap spread levels and volatilities are high.

The approach to spread estimation used in these studies is based on default probabilities calibrated to historical default data. This approach requires an estimate of the credit risk premium. In contrast, we calibrate the iSpread model directly to the risk-neutral measure. Relative value is assessed cross-sectionally from regularly updated market spreads

[1] Goldberg et al. (2007) provides additional references.

and no estimate of the risk premium is required. This is analogous to the original approach to structural modeling taken in Merton (1974). However, the single factor in the Merton model is not adequate to capture the risk in default swap markets. As we show in Goldberg et al. (2007), the two-factor iSpread model is flexible enough to track the dynamics of the default swap market in different economic climates. The risk-adjusted performance metrics in our analysis also provide a window into credit to the community of active equity managers.

Finally, Das et al. (2007) calibrate regression models using accounting and market data, and assess their effectiveness at ranking default swap spreads. While they do not provide performance metrics, they report that a comprehensive model that utilizes both accounting and market data is important in determining rank ordering and future direction of default swap spreads. Tang and Yan (2006) study the impact of a number of factors, including bid–offer spreads, that affect liquidity in the default swap market. They find an average ratio of the bid–offer spread to default swap level equal to 23% (19% median) over the period 1999–mid-2005. This is much larger than the bid–offer spreads that we find in our vendor data, and may be attributable to time variation in bid–offer spreads or the use of quotes from a single dealer as opposed to best bid–offer quotes available in the market. They also find that bid–offer spreads increase with default swap spread levels, which corroborates our transaction cost model, though they do not report any nonlinearity in levels.

2 Model and Data

2.1 The iSpread Model

The iSpread model is an empirical implementation of the I^2 incomplete information structural model, developed in Giesecke and Goldberg (2004). The I^2 model is a first passage model with an unobservable random default barrier. Default occurs when firm value falls below the unobservable default barrier $\mathcal{D}$ or, equivalently, when firm value normalized by V, its value at time 0, falls below *firm leverage* $L = \mathcal{D}/V$. Thus, if M_T denotes the minimum of firm value on $[0, T]$, the probability of default on the horizon $[0, T]$ is given by

$$P\left(\frac{M_T}{V} < L\right) = \int \Psi_T(L)\, dF(L) \tag{1}$$

F is the cumulative distribution function of the effective leverage and $\Psi_T(x)$ is the first passage probability that $M_T/V \leq x$. This shows that the I^2 model is a weighted average or a *mixture* of first passage models (see Figure 1).

Goldberg et al. (2007) simultaneously calibrate the two-factor I^2 model to equity and default swap markets. They show that I^2 is flexible enough to model the dynamics of the default swap markets, and the results of their calibration are applied to portfolio construction below.

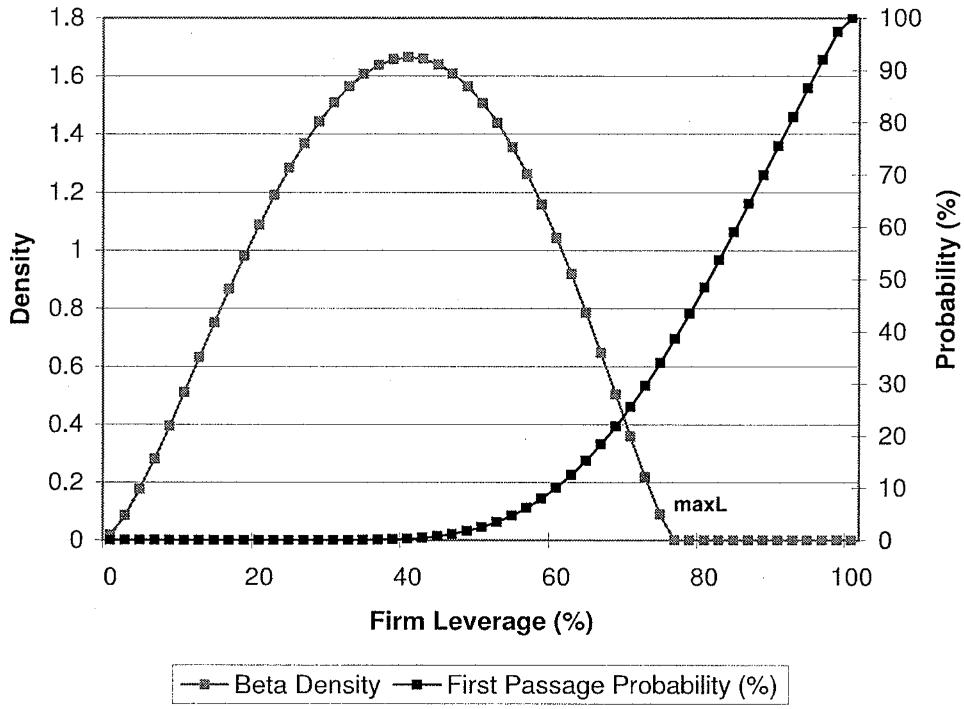

Figure 1: I^2 as a mixture.

2.2 Data

We use default swap spread quotes provided by Credit Market Analysis (CMA) based in London. These are indicative end-of-day quotes (or firm quotes when available) collected from a consortium of brokers and dealers. The data are sorted into 16 calibration groups for estimation and four additional groups for extrapolation on the basis of domicile, sector classification, and coarse quality. We aggregate data by sector, leading to calibration groups such as US, Investment Grade, Consumer Discretionary. Sparsely populated groups are further aggregated. A complete list of our calibration groups is in Table 2 in the appendix. On June 15, 2006 the group sizes in the U.S. range from US-GROUP02-IG with 17 credits to US-GROUP02-HY with 55 credits. The average calibration group has 36 credits. Recovery rates are estimated using a database of post-default bond prices from Moody's.

2.3 Calibration

The model is recalibrated three times per month. Model spreads and other derived data are estimated daily using current model parameters and market data that are updated daily.

3 Active Management of Default Swaps

We use traditional active management principles[2] to evaluate the strength of the trading signal generated by the residuals. The results lead to portfolio strategies that rely on the ability to short credit, which is easily done by buying protection in the default swap market. Since trading costs are minimal, long-short strategies can be run with little capital outlay. If invested capital is measured on an absolute return basis, the manager can attach the active return to that achieved by a fully invested benchmark, such as LIBOR. This allows tailoring of the leverage used in the long-short portion of the portfolio to suit investor preferences. It follows that the analysis of long-short strategies applies to long-only credit portfolio management. The active position in a long-only manager's portfolio can be viewed as a long-short portfolio, and it can be analyzed independently.

The time t residual for credit i is defined as:

$$\text{residual}(i,t) = \text{market spread}(i,t) - \text{model spread}(i,t). \tag{2}$$

It serves as a forecast for excess returns on the credit for the subsequent period. We standardize the residuals across each region-quality and year bucket:

$$Z(i,t) = \frac{\text{residual}(i,t) - \mu_{residual}}{\sigma_{residual}} \tag{3}$$

where $\mu_{residual}$ and $\sigma_{residual}$ are the mean and standard deviation of the spread residuals across the bucket.

The active return $R^a(i,t)$ for credit i on date t with respect to an equally weighted index based on its calibration group is:

$$R^a(i,t) = R(i,t) - \beta(i,t)R(t) \tag{4}$$

where $R(i,t)$ is the period return to name i on date t, $R(t)$ is the period return to the index on date t, and $\beta(i,t)$ is sensitivity of the ith name to the index.[3]

In order to filter outliers returns are standardized in a similar manner to model residuals.

$$Y(i,t) = \frac{R^a(i,t) - \mu_{return}}{\sigma_{return}} \tag{5}$$

where μ_{return} and σ_{return} are the mean and standard deviation of the active returns across the bucket.

The information coefficient of a region–quality portfolio is the correlation between the standardized active returns and standardized residuals.

$$IC(t) = \text{corr}(Y, Z) \tag{6}$$

[2] A basic reference is Grinold and Kahn (2000).

[3] Historical betas are estimated using a one–year half-life. Consequently, information ratios are calculated only for 2005 and 2006.

An estimate for the portion of excess return that can be captured for a single credit is given by

$$\hat{R}^a = \sigma \cdot IC \cdot Z \tag{7}$$

where σ is the volatility of excess return. We standardize formula (7) by σ to obtain the single name Information Ratio:

$$IR = IC \cdot Z \tag{8}$$

The portfolio information ratio is given by

$$IR_P = IC \cdot \sqrt{N \cdot T} \tag{9}$$

where N is the number of securities in the portfolio and T is the number of times per period that the portfolio is rebalanced.[4] If $IC > 0$, the information ratio tends to increase with the breadth of the strategy, given by the product $N \cdot T$.

We find that estimation of the information coefficient is very sensitive to outliers in the dataset with cases where a handful of observations explain about 50% of the information coefficient for a given region–quality–year bucket. To prevent estimation bias, observations of either standardized score with absolute values larger than 3 are discarded.[5]

Figures 2 and 3 use an estimate of the information coefficient based on formula (6) to show the dependence of the information ratio on the z-score for each region–quality portfolio. The region–quality portfolio information ratios for 2005 and 2006 are computed using formula (9) and are displayed in Figure 4. The highest information ratio of 4.4 is obtained for the EU Investment Grade portfolio in 2006. The lowest information ratio is obtained in 2006 by the European Unrated portfolio, which had a negative information coefficient. Table 1 displays the information coefficients and portfolio sizes[6] underlying the information ratio estimates.

This analysis points to a strategy that involves selling protection (receiving a premium) on credits with positive z-scores and buying protection (paying a premium) on credits with negative z-scores.[7] Below, we implement an instance of this strategy in which credits in the top and bottom quartiles of each calibration group are traded.

4 Long-short Strategies: Portfolio Construction and Empirical Results

4.1 Credit Selection and Strategy Outline

The strategies we consider are predicated on a time–dependent ranking of names from cheapest to richest. Here, we give a detailed description of the ranking algorithm and

[4] This estimate follows from Formula (8) assuming forecasts are independent.

[5] The estimated information coefficient is distorted by observations that have both large residuals and large active returns. By contrast, realized information ratios (calculated later in the paper) depend only on the return.

[6] The estimated size of each region–quality portfolio takes account of data quality filtering.

[7] This strategy can be enhanced by ignoring credits with small absolute z-scores as they do not contribute much to portfolio information ratios. While this lowers the breadth of the strategy, it raises the product of the information coefficient with the z score. These effects are at cross purposes.

portfolio construction strategy that was applied over the study period.

1. Compute the residual of each name using formula (2).
2. Drop names with systematic residuals.

   A *systematic residual* is the average over three lagged monthly points if all errors have the same sign, zero otherwise. Roughly ten percent of the estimation universe is eliminated in this step.[8]
3. Create portfolios based on region, coarse quality, and sector.
4. Rank the names in each portfolio by the difference between market and model spreads and sort them into three subportfolios:

   The top (larger residual) quartile is cheap.

   The bottom (smaller residual) quartile is rich.

   The middle half is fairly priced and therefore ignored.
5. Determine notional weights.

   We explore several variants, all intended to neutralize exposure to broad market movements.
6. Trade

   Sell protection on cheap names (equivalent to buying cheap bonds).

   Buy protection on rich names (equivalent to selling rich bonds).
7. Rebalance regularly and accumulate monthly mark-to-market changes.

[8]Typical credits in this set include leveraged buyout targets and other special cases for which there are not relevant market data.

Table 1: Information Ratio Estimates based on Information Coefficients and 12 trades per year

Region	Quality	Year	Information Coefficient (IC)	Number of Credits (N)	Information Ratio (IR)
US	Investment Grade	2005	0.06	195	2.9
		2006	0.044	195	2.1
	High Yield	2005	-0.024	65	-0.7
		2006	0.115	65	3.2
EU	Investment Grade	2005	0.092	80	2.9
		2006	0.141	80	4.4
	Not Rated	2005	0.048	45	1.1
		2006	-0.045	45	-1.0

4.2 Base Strategies

Strategy profits and losses are presented as earnings per long dollar of notional. Ex-post information ratios are calculated to assess the tradeoff between strategy return and volatility.

4.2.1 Carry-neutral

Portfolios are rebalanced monthly and notional weights are chosen to neutralize carry. The ratio of rich to cheap notional weight ranges between 1.5 and 2.5. Time series of these ratios for three portfolios are in Figures 10, 11, and 12.

Figure 5 shows the strategy earnings aggregated by region and quality. The results were overwhelmingly positive with the largest gains in US High Yield in 2004. Portfolio information ratios averaged over region and quality are in Figure 6.

Figures 7– 9 provide a more detailed analysis of the carry-neutral strategy. Figure 7 displays the earnings for the US Investment Grade portfolios. Market turmoil resulting from the General Motors and Ford downgrades and the default of Delphi explain the poor performance of the consumer discretionary portfolio in 2005.

4.2.2 Beta-neutral

Each month, we calculate the historical beta to the relevant region–quality benchmark for the rich and cheap portfolios in each calibration group.[9] The ratio of rich to cheap portfolio notional amounts is determined by the ratio of the corresponding betas.[10] Figures 10, 11, and 12 show the realized timeseries of weights. On average, beta-neutral weights and carry-neutral weights are similar over the historical period studied. However, the beta-neutral weights are smoother, therefore beta-neutral strategies are likely to have smaller rebalancing costs than carry-neutral strategies. Figures 13 and 14 show the beta-neutral earnings and information ratios for region–quality portfolios. The performance is very similar to the carry-neutral performance, with the US Investment Grade portfolio performing better using beta-neutral weights.

4.3 Transaction Costs and Turnover

As illustrated in figures 15 and 16, the carry-neutral rich and cheap portfolios average about 30 percent turnover per month, or approximately 350 percent per year. Below, we estimate the resulting transaction costs and adjust the simulation results accordingly. This exercise is not straightforward due to the data screening techniques we use to ensure a clean representation of market information in our calibration and portfolio strategies. Spreads in our data set are tagged either as observed or derived, and the latter accounts for 10–12% of the data. Derived spreads tend to be stale or noisy and are discarded, leaving a data set that is less consistent than optimal. This process accounts for up to a

[9]Historical betas are estimated using a one-year half-life.

[10]Note that a beta-neutral strategy may have non-zero carry.

third of the turnover, as shown in figures 17 and 18 for the U.S..[11]

Transaction costs are realized as bid-offer spreads, which vary by dealer, by economic climate, and over time. We express bid-offer spreads as a piecewise linear function of default swap spread level. The bid-offer curves are fitted to dealer quotes. A typical estimate from May 2007 is shown in Figure 19. The top representative bid-offer (RBO) reflects dealer spreads. The bottom best bid-offer (BBO) curve reflects best spreads obtained by taking offers and bids from different dealers. The higher interpolated bid-offer (HIBO) curve and lower interpolated bid-offer (LIBO) curve lie between the two extremes.[12]

4.4 Transaction Cost Adjusted Strategies

4.4.1 Adjusting the Carry-Neutral Strategy for Transaction Costs

We use the bid-offer spread curves to generate cost per long dollar notional. We penalize each trade by half the bid-offer spread dictated by the spread level of the traded default swap. The impact on the carry-netural strategy for US portfolios is shown in Figures 20 and 21 and on the European portfolios in Figures 22 and 23. Transaction costs declined over our study period, reflecting the decline in volatility and the trend toward tighter spreads.

Figures 24 and 26 show net profits and losses for the RBO and BBO transaction cost scenarios. These plots can be compared to Figure 5. While transaction costs are likely to be a key consideration in investment grade implementation, non-investment grade portfolios produce substantial returns net of transaction cost.

4.4.2 Mitigating Transaction Costs

We modify the base carry-neutral strategy by holding a credit until it shows a significant return.[13] We construct candidate portfolios in the usual way. For a candidate outgoing credit, we trade only if the profit or loss exceeds a fixed multiple of the transaction cost. We consider integer multiples ranging from 1 to 10 and find that in all cases the transaction costs of the mitigated carry-neutral relative to its base change only slightly. However, the raw profits of the investment grade portfolios tend to increase, while the raw profits for the high yield portfolios tend to decrease.

Figures 28 and 29 show the net impact of this strategy on US Investment Grade and US High Yield portfolios as we vary the multiple required to trigger a trade from 1 to 10.

[11] The precise impact of the missing data on the strategy is impossible to assess. However, assuming a material similarity between our realized strategy and one based on a complete data set, an unknown fraction of the missing data component of turnover would be realized as actual turnover in a complete data set. Thus, one-third is a rough upper bound for the fraction of turnover attributable to missing data. We are experimenting with ways to reduce the component of missing data without sacrificing robustness.

[12] The best bid-offer spread estimates vary over time and throughout the study period, and have tended to lie between the top and bottom curves.

[13] There are many other strategies for mitigating transaction costs. We might decrease the evaluation frequency of one month or rebalance the portfolio only when its average value deviates from an optimum by a specified margin.

4.5 Comparing the Strategies

Figures 30 and 31 show the earnings per long dollar notional and information ratios for the carry-neutral, beta-neutral, and transaction cost adjusted carry-neutral strategies for 2005 and 2006. The performance of these strategies is strong in most regions, investment qualities, and time periods studied. The highest earnings were achieved for the US High Yield portfolios, and the highest information ratios obtained for the Europe investment grade portfolios. The returns for the European unrated portfolios were negative for all the strategies in 2006 although they were strongly positive in 2005. In the investment grade universe, transaction costs may be a key consideration.

5 Concluding Remarks

The default swap market expands the opportunities available to the traditional credit investor. It provides a means to inexpensively take short credit positions, and it benefits from the absence of constraints on leverage innate to an unfunded derivatives market. This paper assesses the performance of the I^2 structural model and implements long-short strategies that naturally arise by considering the difference between market and model default swap spreads as an indicator of relative value. We provide detailed assessment of transaction costs and explore mitigation strategies that can lead to a successful implementation.

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A Calibration Groups

Table 2: Calibration Groups

Calibration Group	Description
US-CONSDISC-IG	Consumer Discretionary
US-ENERGY-IG	Energy
US-FINANCE-IG	Finance
US-INSURANC-IG	Insurance
US-GROUP01-IG	Con. Staples, Health
US-GROUP02-IG	Info. Tech., Telecom
US-INDUST-IG	Industrials
US-MATERIAL-IG	Basic Materials
US-UTILITY-IG	Utilities
US-GROUP01-HY	Cons. Disc., Cons. Staples, Health
US-GROUP01-NR	Cons. Disc., Cons. Staples, Health
US-GROUP02-HY	Energy, Ind., Util., Matl., Info. Tech., Telecom, Finance
US-GROUP02-NR	Energy, Ind., Util., Matl., Info. Tech., Telecom, Finance
EU-FINANCE-IG	Finance
EU-GROUP01-IG	Cons. Disc., Cons. Staples, Health
EU-GROUP01-NR	Cons. Disc., Cons. Staples, Health
EU-GROUP01-HY	Cons. Disc., Cons. Staples, Health
EU-GROUP02-IG	Energy, Ind., Util., Matl., Info. Tech., Telecom
EU-GROUP02-NR	Energy, Ind., Util., Matl., Info. Tech., Telecom, Finance
EU-GROUP02-HY	Energy, Ind., Util., Matl., Info. Tech., Telecom, Finance

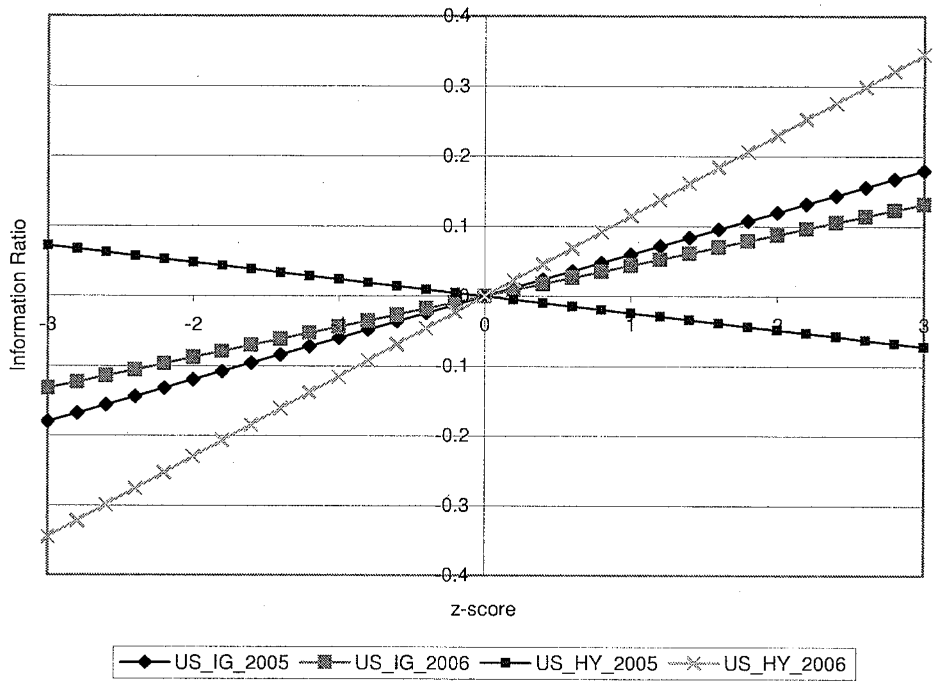

Figure 2: Information ratios for US-IG and US-HY credits as a function of z-score. The slope of the line corresponding to a region–quality group is its information coefficient.

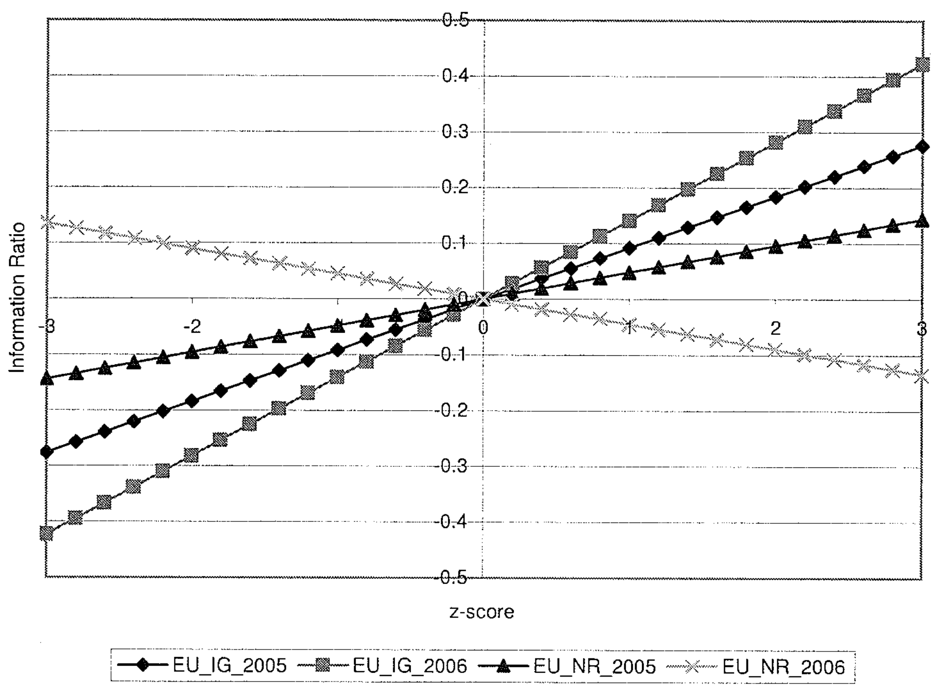

Figure 3: Information ratios for EU-IG and EU-NR credits as a function of z-score. The slope of the line corresponding to a region–quality group is its information coefficient.

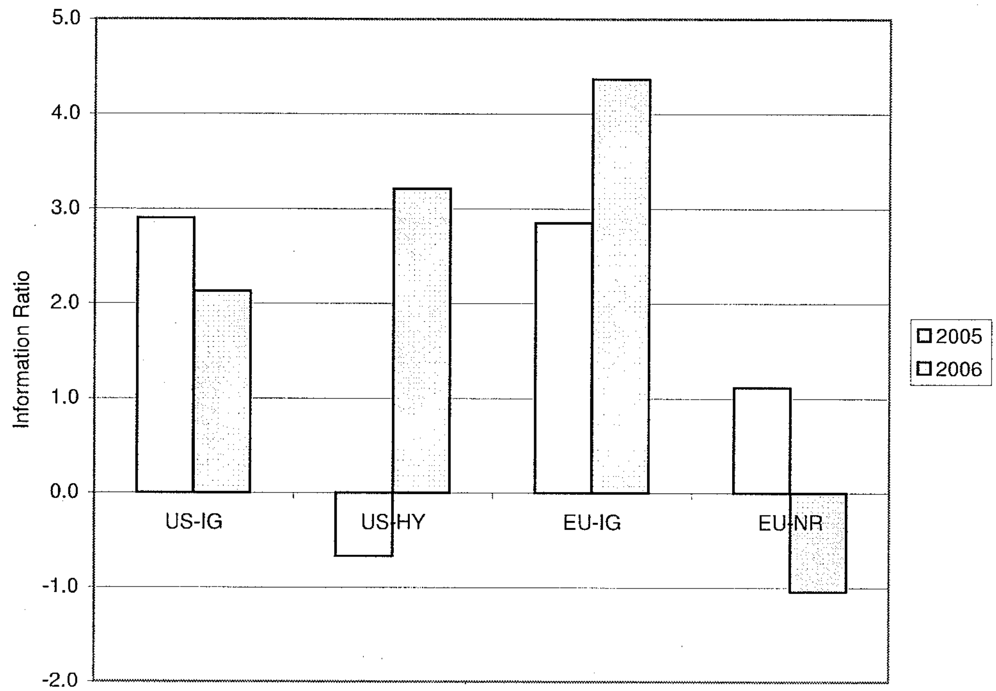

Figure 4: Residual information ratios.

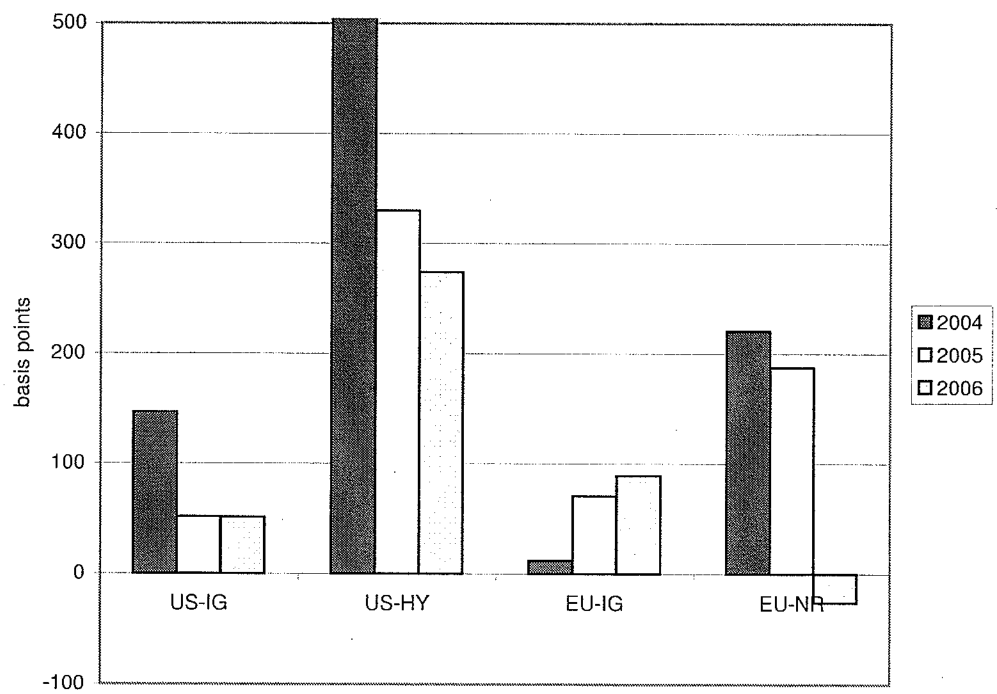

Figure 5: Carry-neutral earnings per long dollar notional.

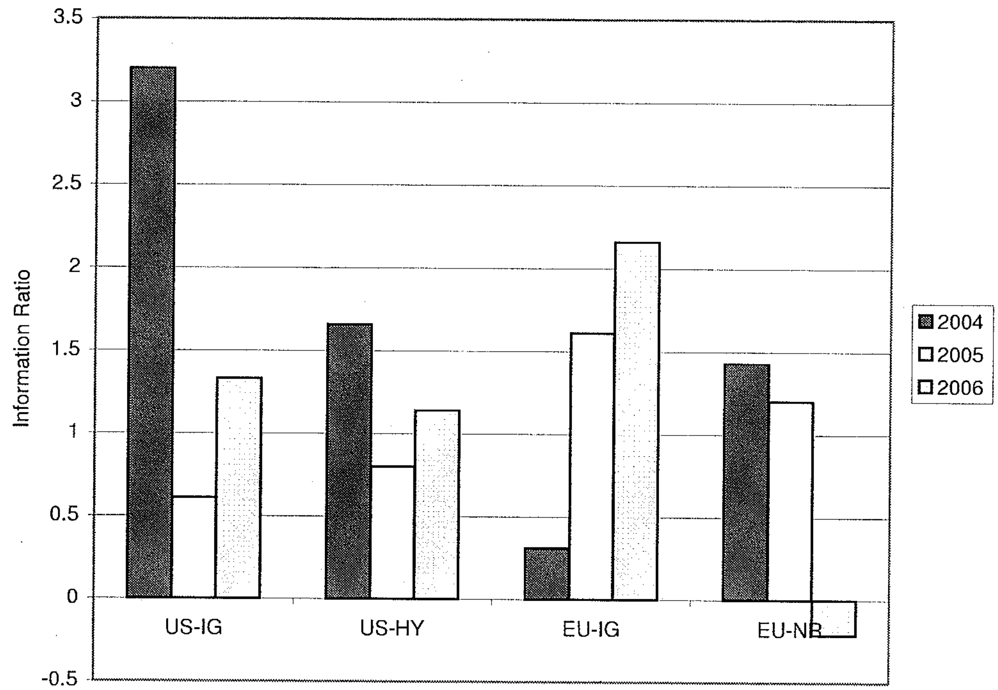

Figure 6: Carry-neutral information ratios.

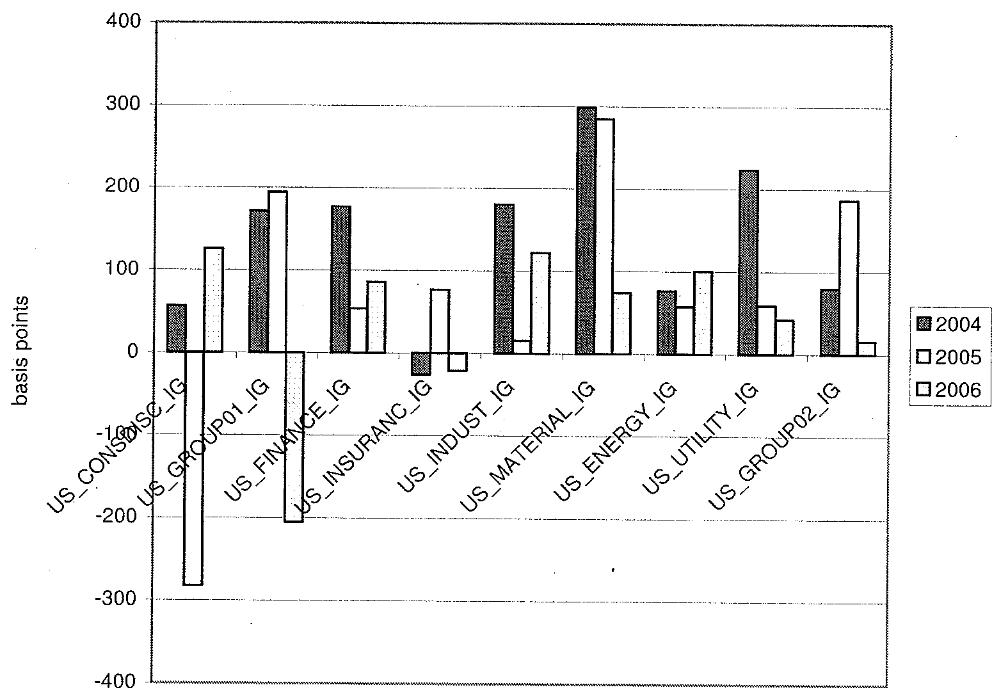

Figure 7: Carry-neutral earnings per long dollar notional: US Investment Grade.

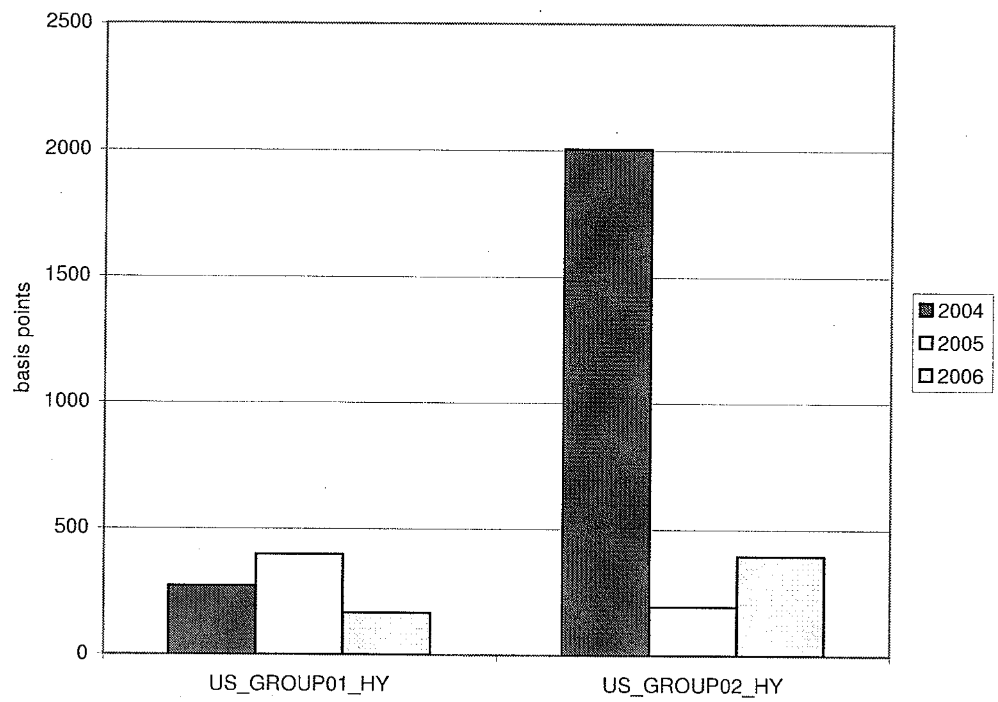

Figure 8: Carry-neutral earnings per long dollar notional: US High Yield.

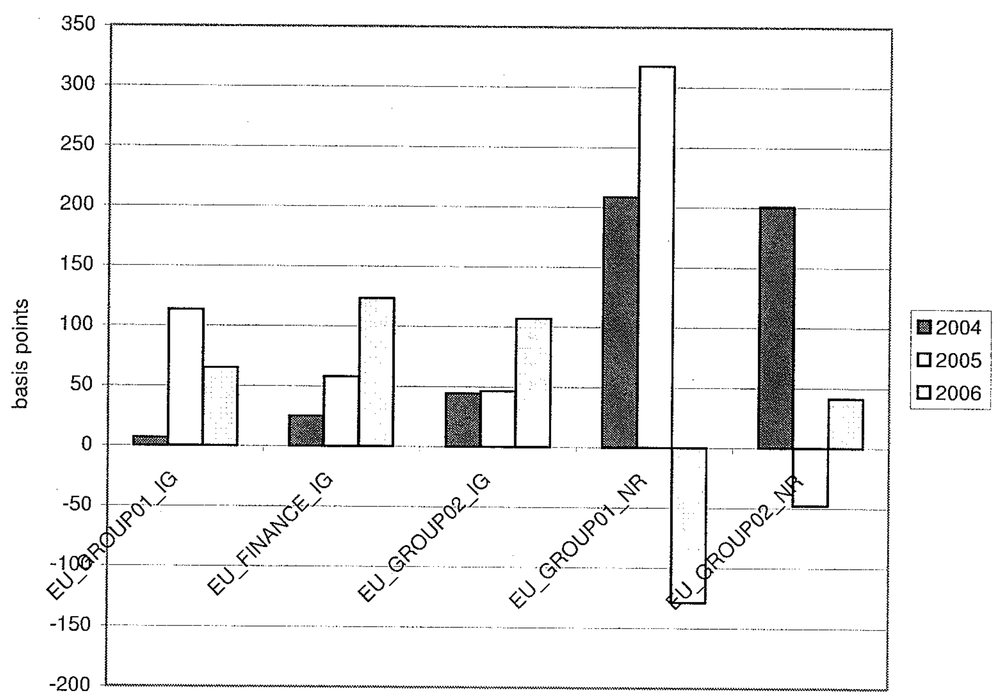

Figure 9: Carry-neutral earnings per long dollar notional: EU/UK.

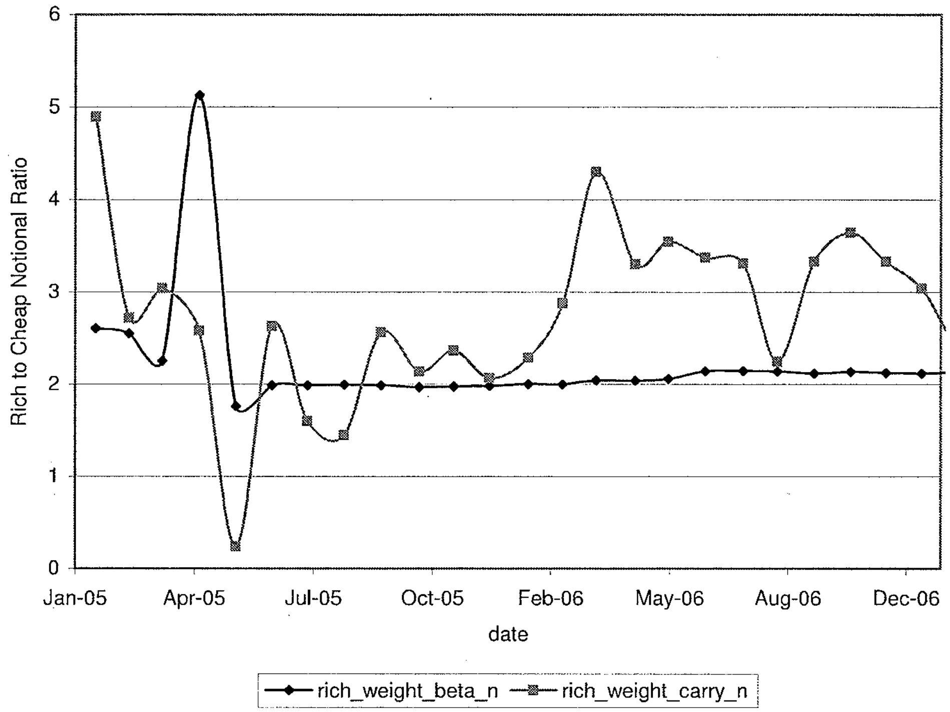

Figure 10: Rich to cheap notional weight comparison: US IG Consumer Discretionary.

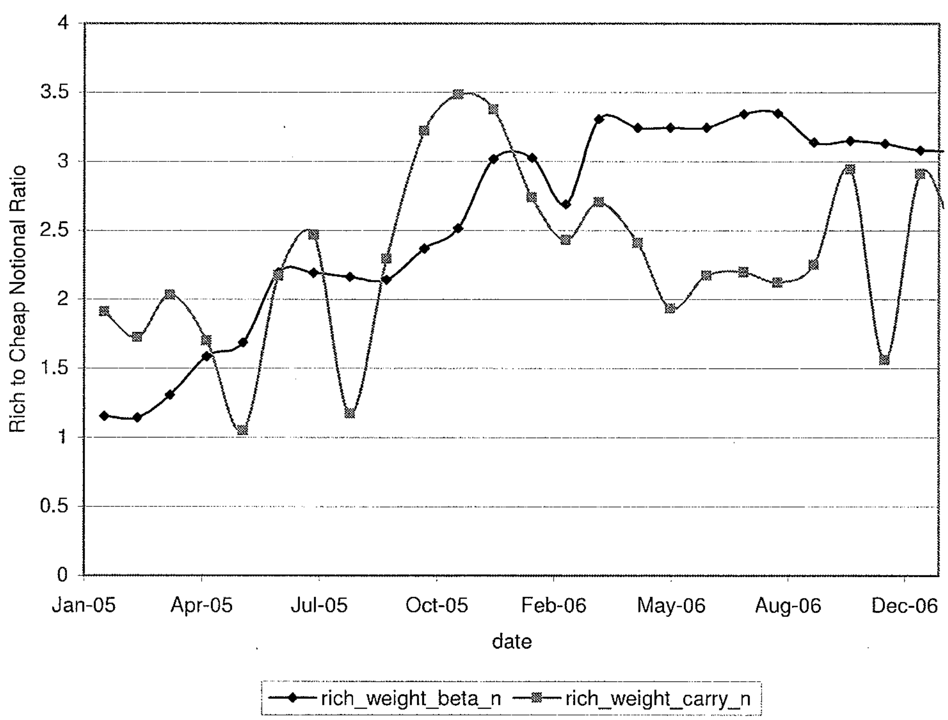

Figure 11: Rich to cheap notional weight comparison: US IG Industrials.

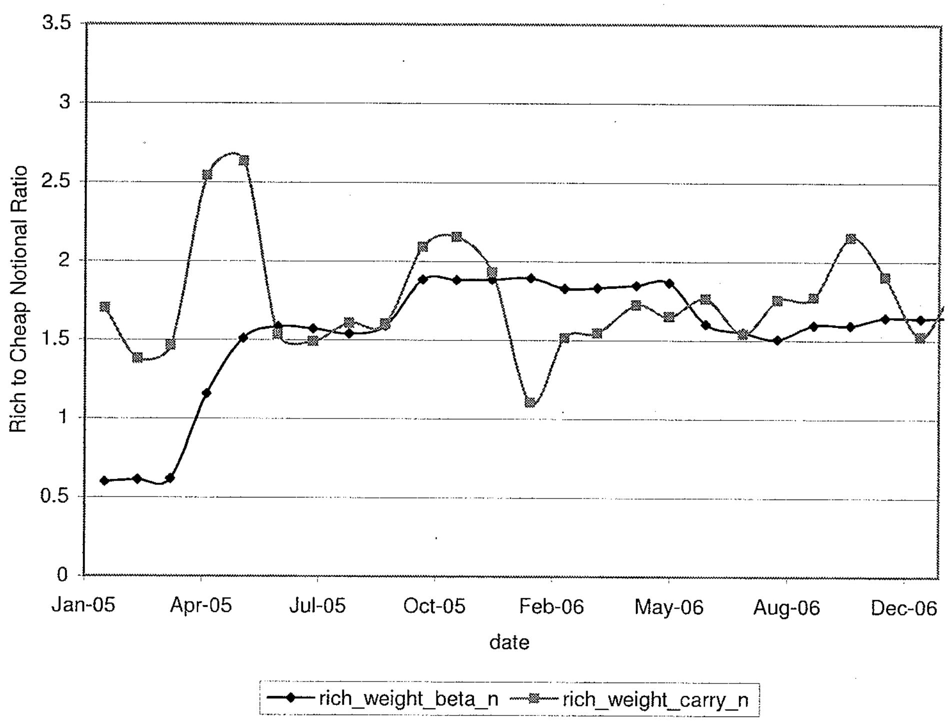

Figure 12: Rich to cheap notional weight comparison: US High Yield Group 2.

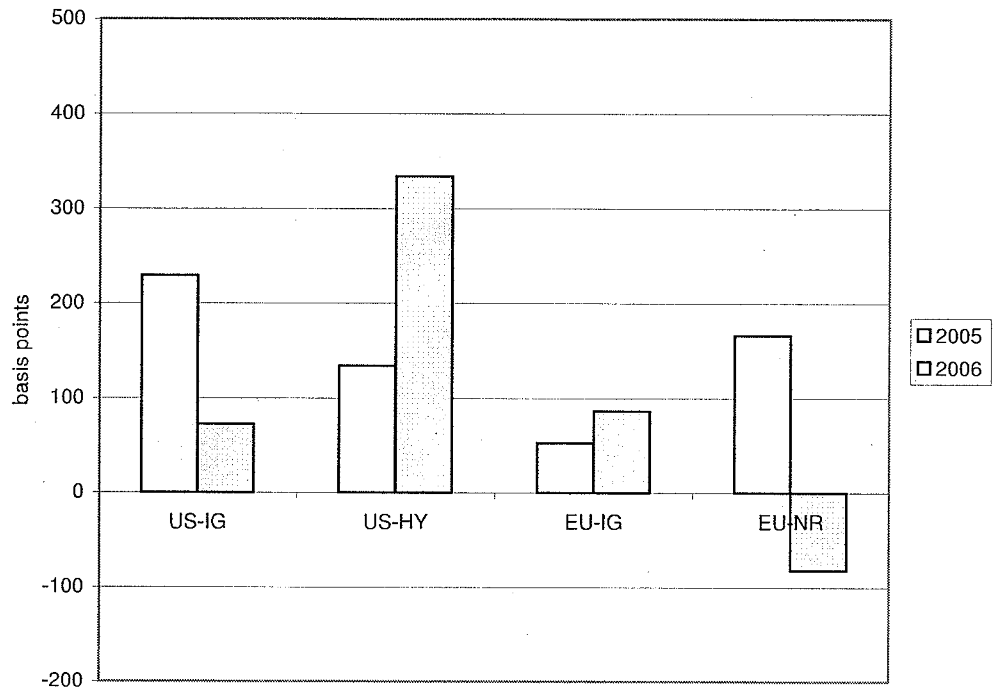

Figure 13: Beta-neutral earnings per long dollar notional.

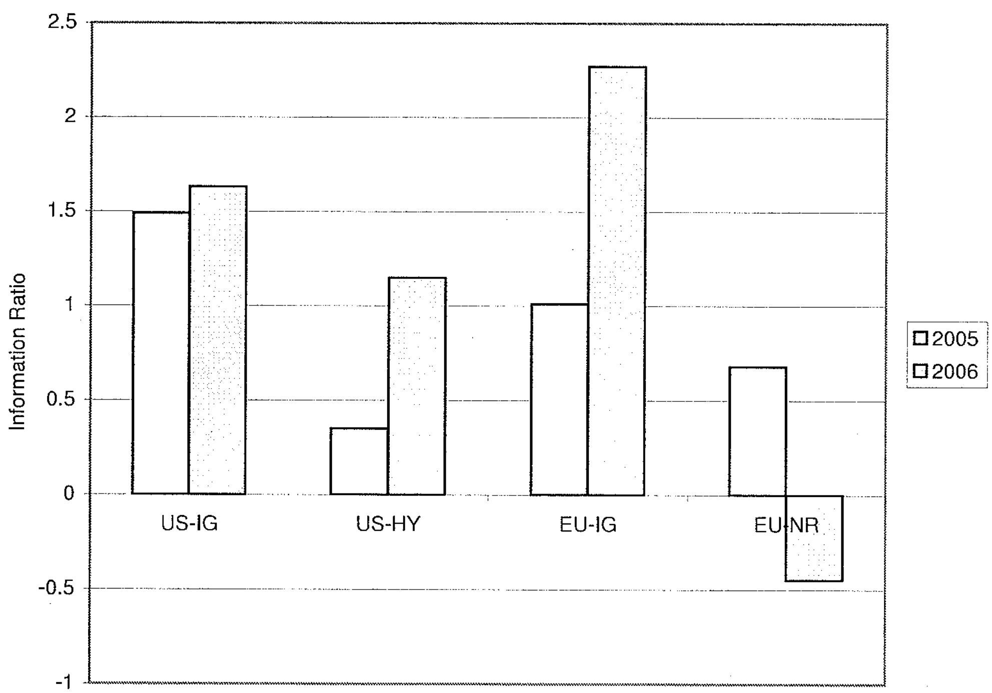

Figure 14: Beta-neutral information ratios.

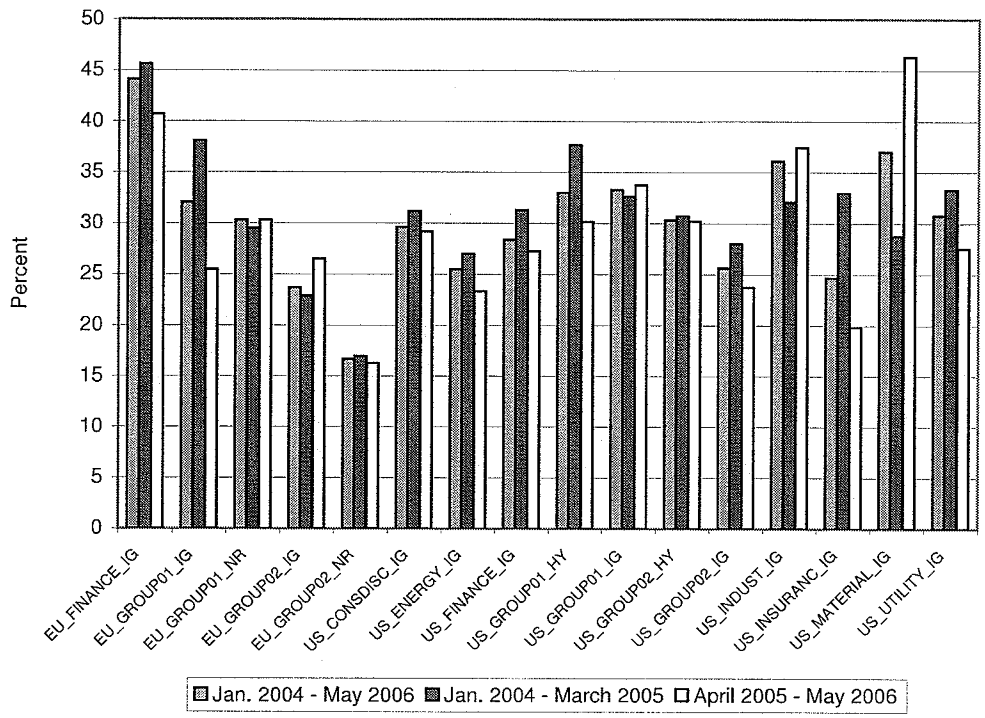

Figure 15: Average monthly turnover rate in percent for rich portfolio.

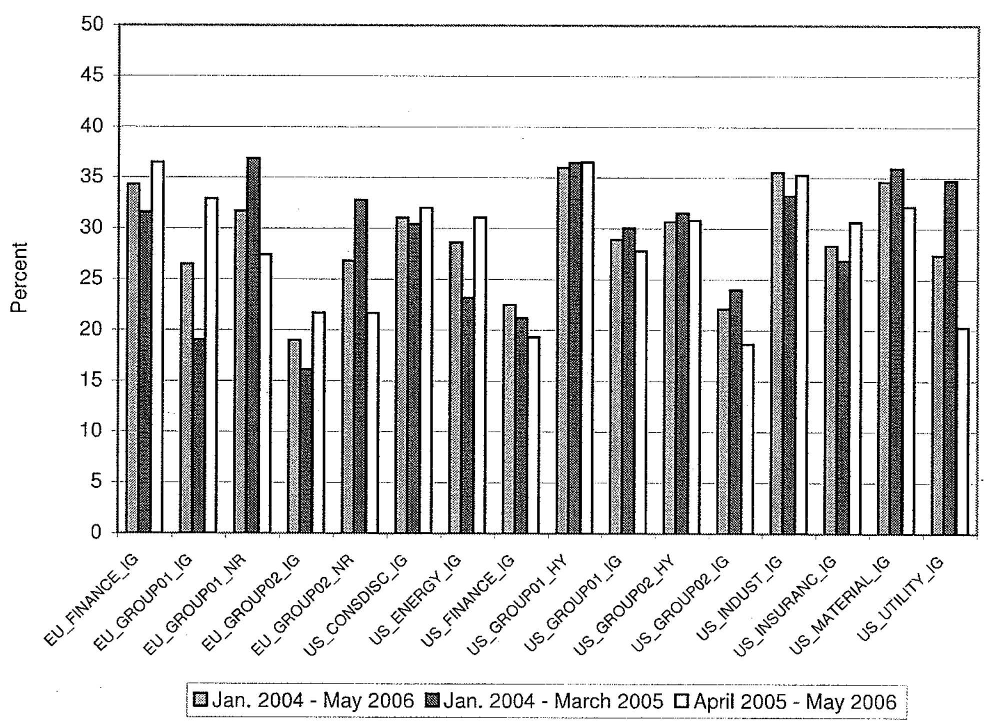

Figure 16: Average monthly turnover rate in percent for the cheap portfolio.

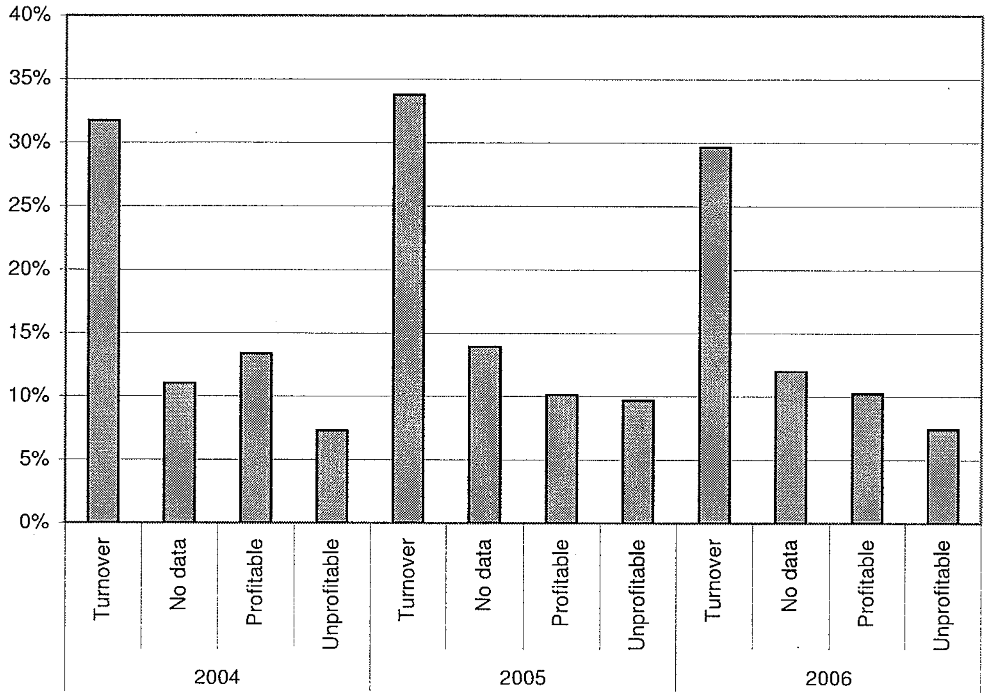

Figure 17: Average monthly turnover rate for US rich portfolio.

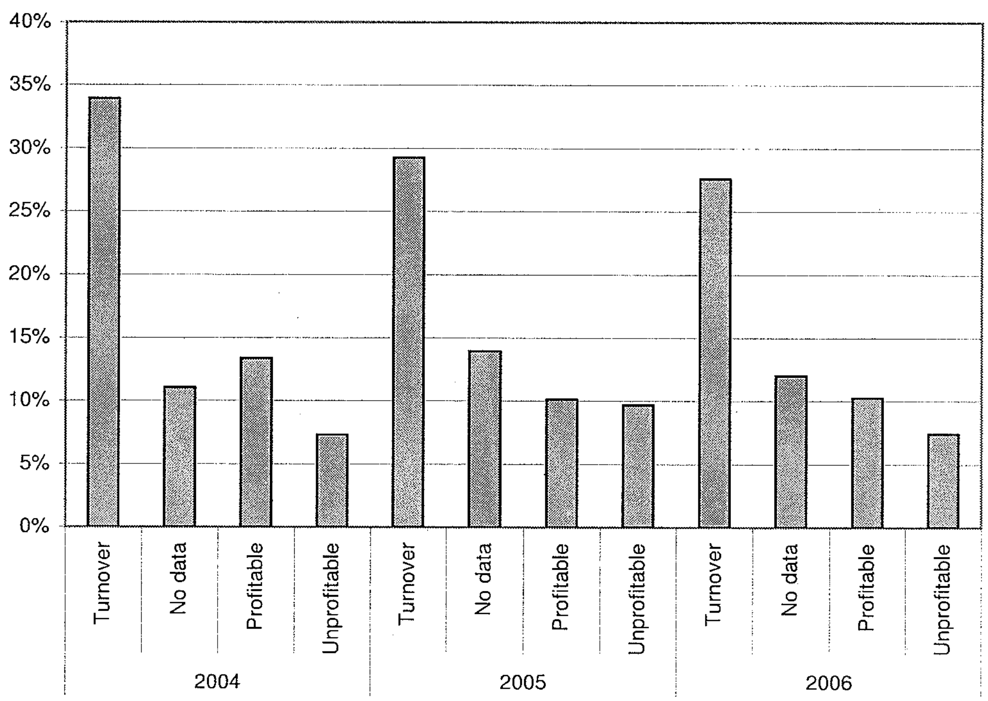

Figure 18: Average monthly turnover rate for the US cheap portfolio.

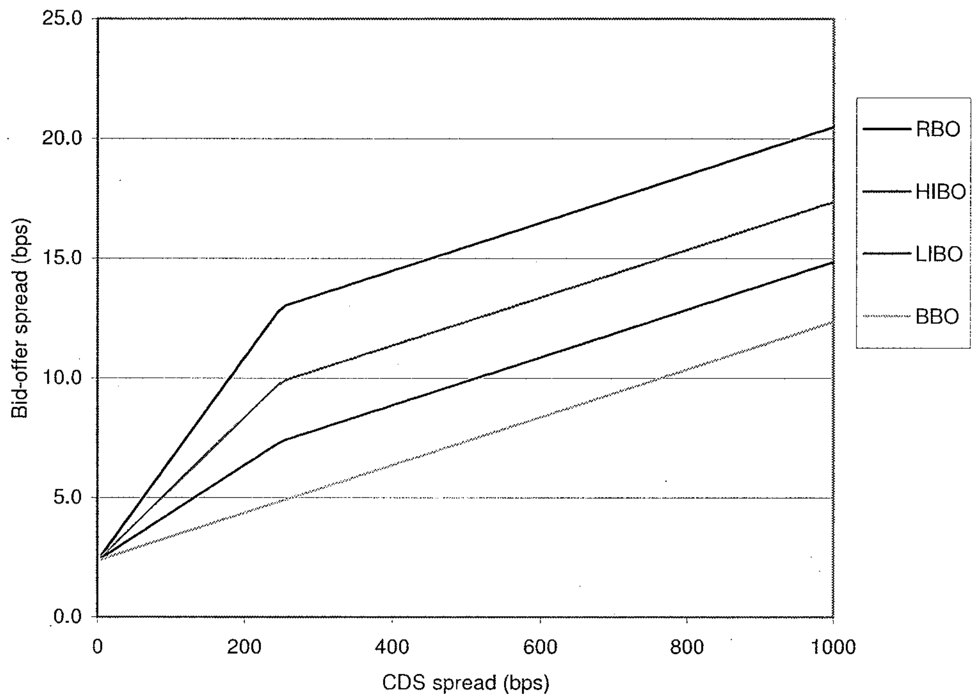

Figure 19: Estimated bid-offer spreads curve. The top curve is based on representative bid-offer (RBO) spreads deals. The bottom curve is based on the best bid-offer (BBO) spreads obtained by taking the difference between offers and bids from different dealers. The higher interpolated bid-offer (HIBO) and lower interpolated bid-offer lie in between the two extremes. These bid-offer scenarios are used to adjust our base strategy for transaction costs.

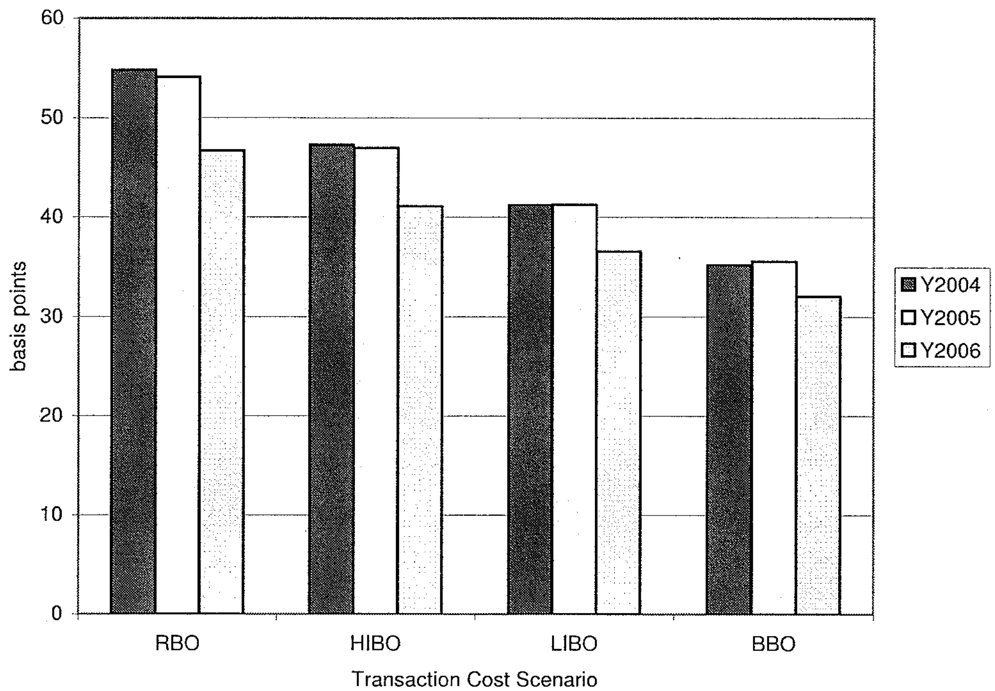

Figure 20: Carry-neutral transaction costs per long dollar notional: US Investment Grade.

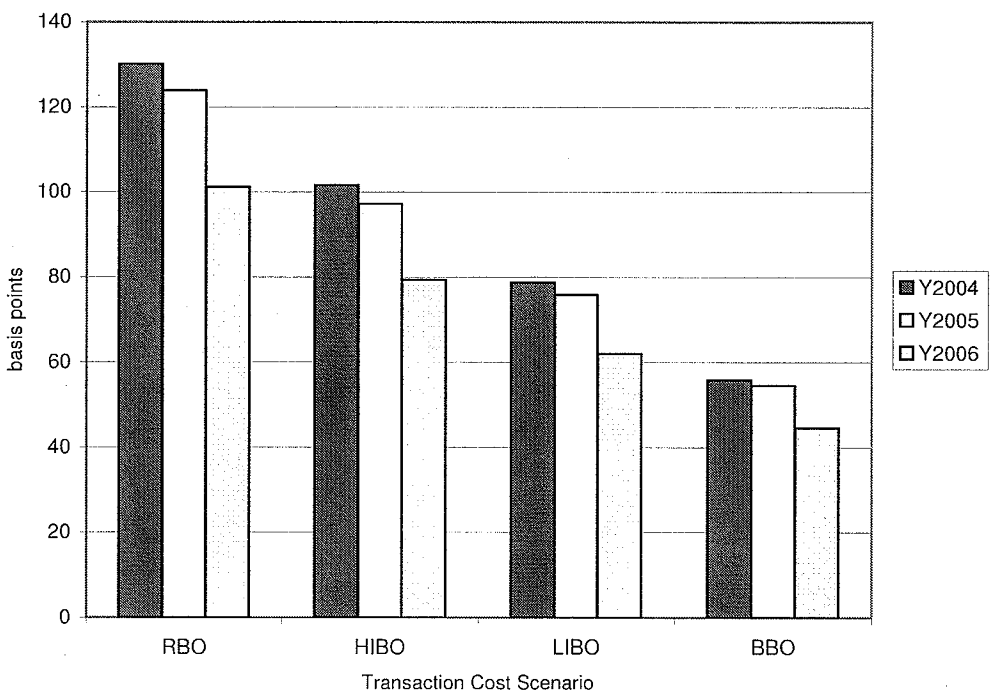

Figure 21: Carry-neutral transaction costs per long dollar notional: US High Yield.

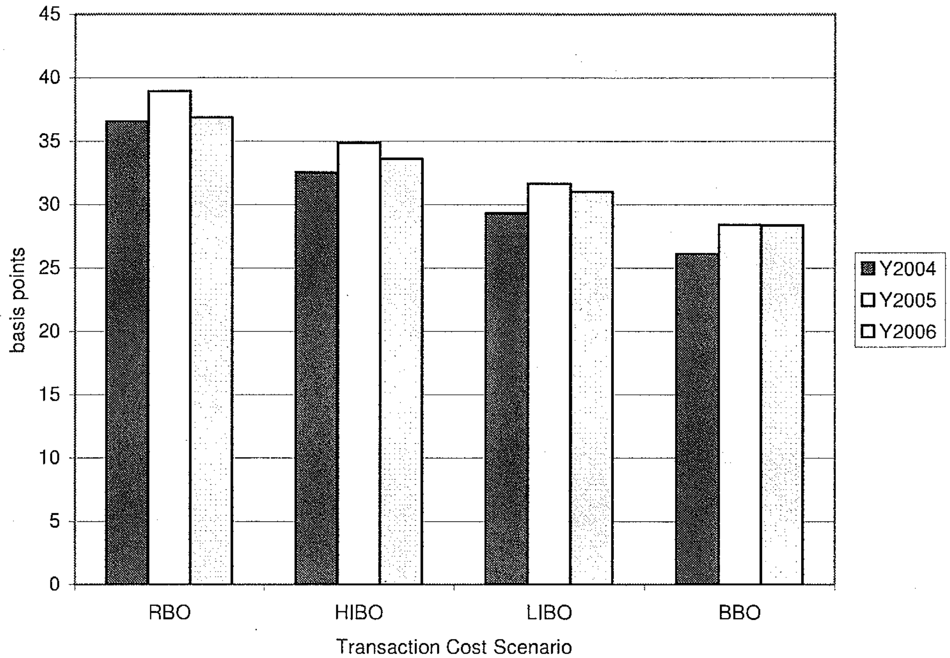

Figure 22: Carry-neutral transaction costs per long dollar notional: Europe Investment Grade.

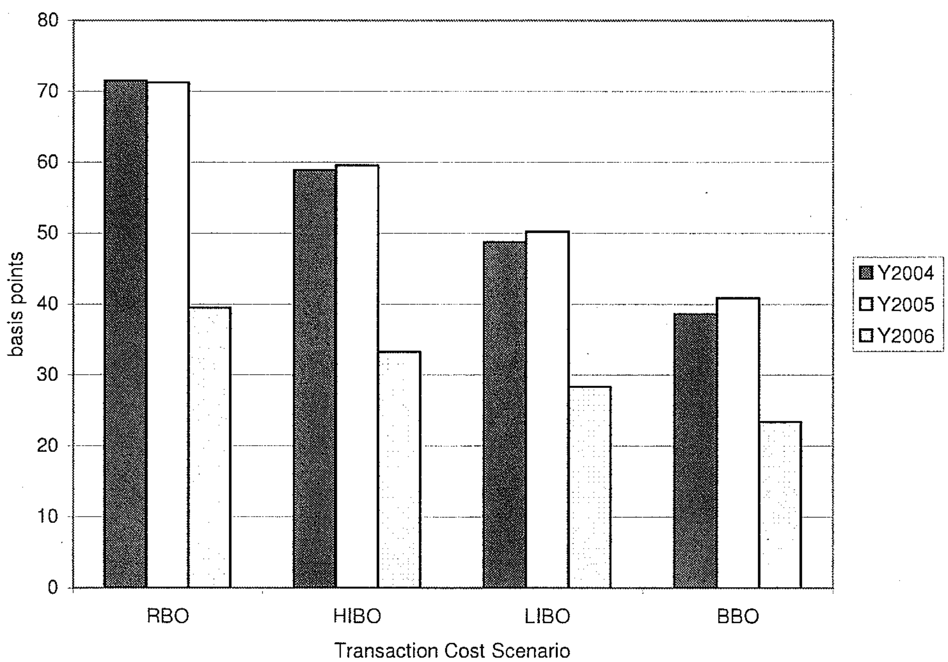

Figure 23: Carry-neutral transaction costs per long dollar notional: Europe Unrated.

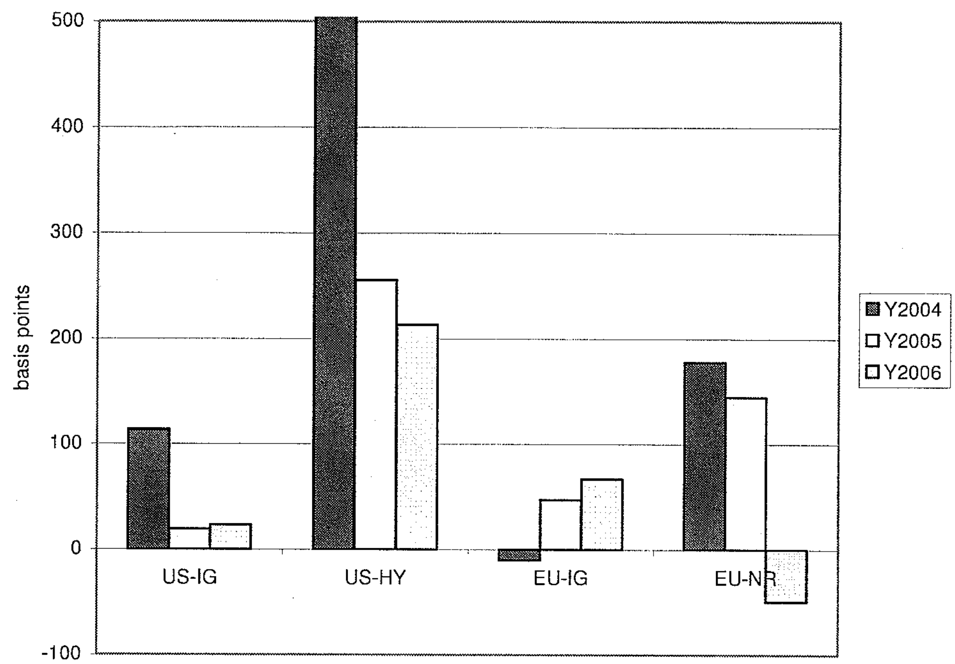

Figure 24: Carry-neutral earnings adjusted with RBO transaction costs per long dollar notional.

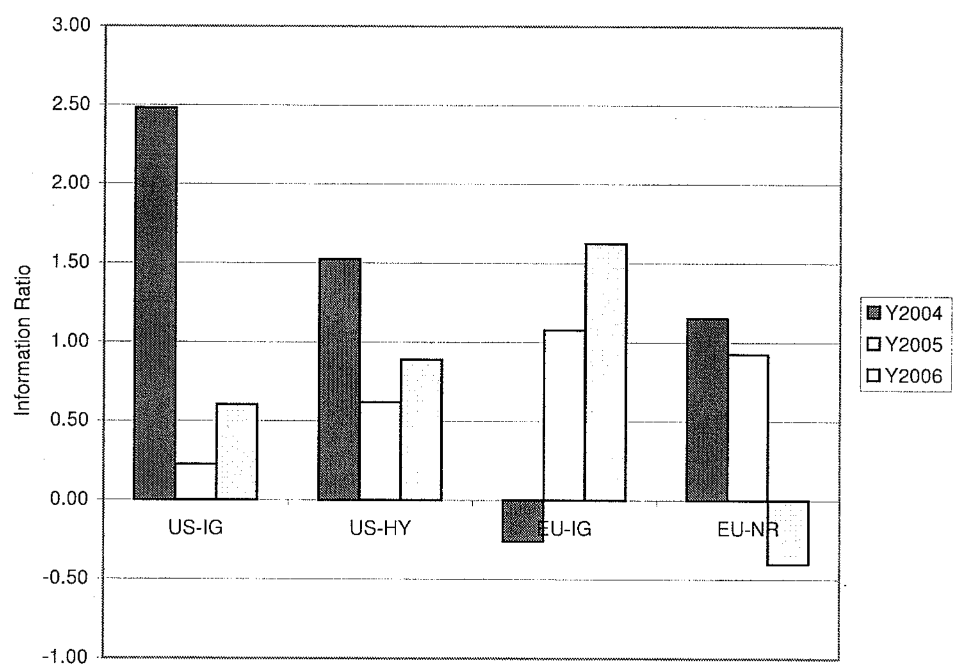

Figure 25: RBO adjusted carry-neutral information ratios.

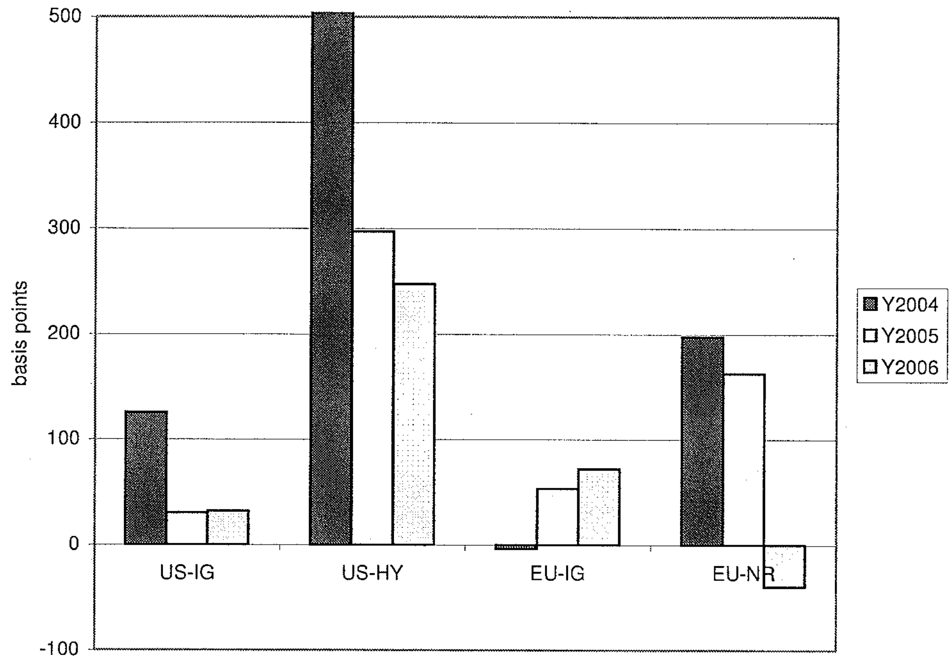

Figure 26: Carry-neutral earnings adjusted with BBO transaction costs per long dollar notional.

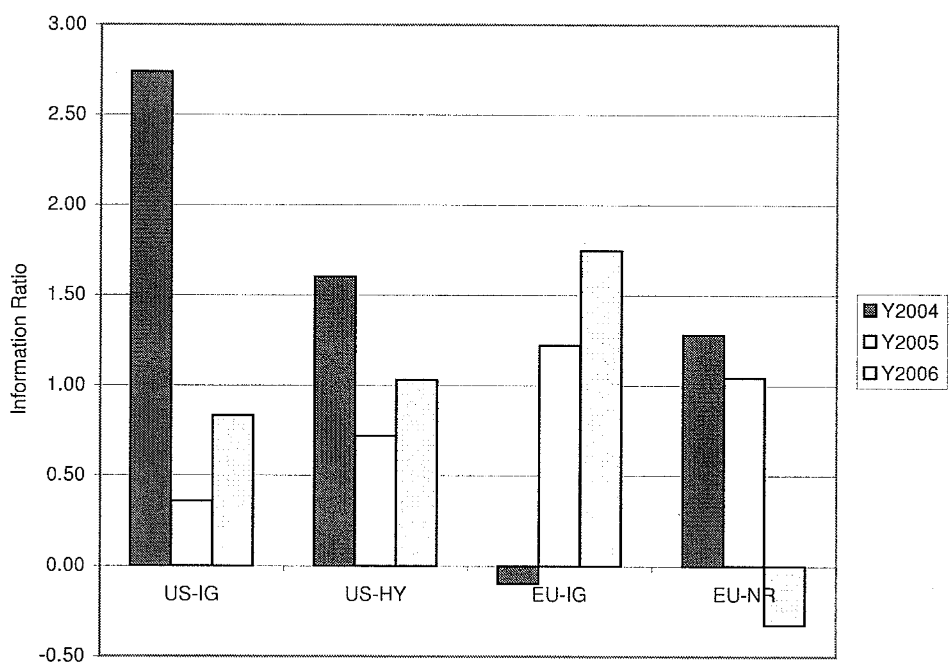

Figure 27: BBO adjusted carry-neutral information ratios.

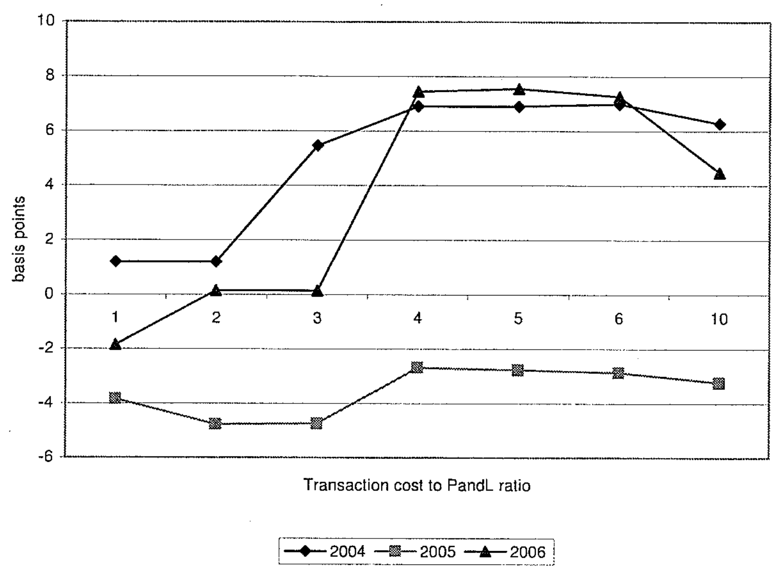

Figure 28: Difference in earnings per long dollar notional between the transaction adjusted carry-neutral strategy with and without mitigation: US Investment Grade. The mitigated strategy outperformed the unmitigated strategy in 2004 and underperformed in 2006. The results were mixed for 2005, outperforming for low multipliers and underperforming for high multipliers.

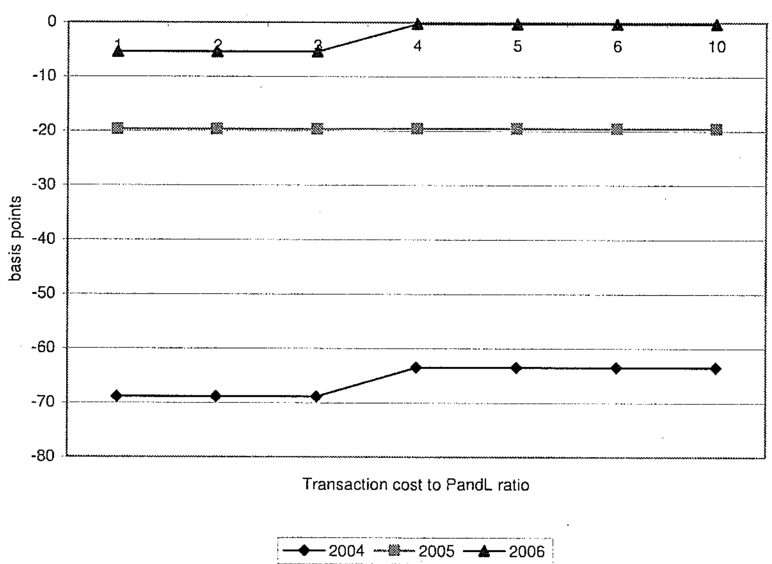

Figure 29: Difference in earnings per long dollar notional between the transaction adjusted carry-neutral strategy with and without mitigation: US High Yield. The mitigated strategy uniformly underperformed the base strategy.

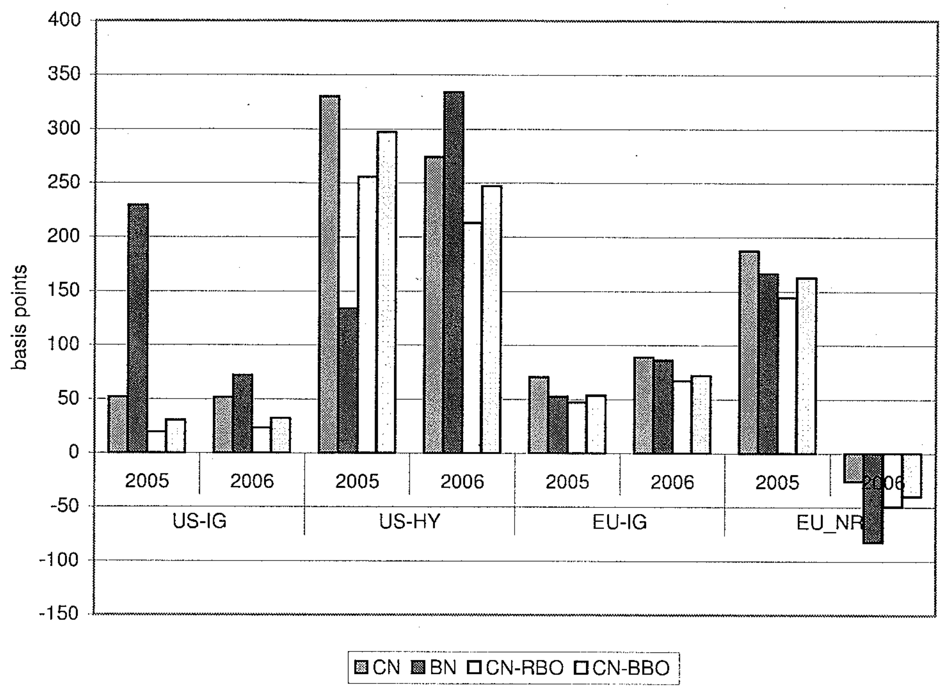

Figure 30: Earnings for the carry-neutral, beta-neutral, RBO adjusted carry-neutral, and BBO adjusted carry-neutral strategies.

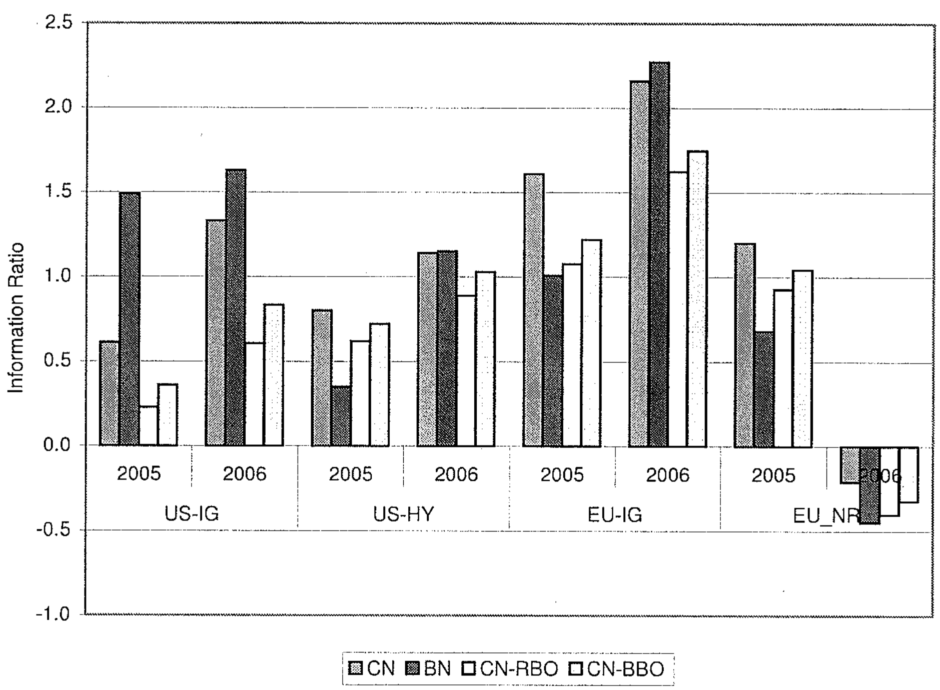

Figure 31: Information ratios for the carry-neutral, beta-neutral, RBO adjusted carry-neutral, and BBO adjusted carry-neutral strategies.